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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The financial ecosystem has evolved over the years, particularly because of the fast pace of digital technology, computing power and data analytics developments. The heart of this revolution is Artificial Intelligence, a vast and quickly developing field of computer science that includes machine learning and predictive analytics. Such technologies are not restricted to research labs or tech firms but are being more widely integrated into the everyday business of world finance-related institutions.

Traditionally, skilful and experienced professionals like the financial analysts, portfolio managers make investment decisions based on their skill, experience and judgment. This paradigm was first significantly disrupted by the great progress made in computer-based quantitative models in the 1970s. Companies such as Goldman Sachs and Morgan Stanley started hiring quantitative analysts, also known as "quants," who devised mathematical models for pricing, risk analysis and trading strategies.

The computing techniques available at the time, however, were constrained by the available computing power and data. Models were generally simple, linear and derived from simplified assumptions about market behaviour and used relatively small datasets. A qualitatively new and much more powerful type of computational intelligence is a revolution that has taken place when machine learning models can learn to perform well without being explicitly programmed to recognize complex patterns. The revolution, together with development of big data, has brought new opportunities to investment decision-making.

In addition to trading desks within institutional energy companies, AI has made its way into retail investment via Robo-advisors' digital platforms, which serve clients by leveraging algorithms to deliver automated and personalized investment advice and portfolio management at a lower cost than conventional investment firms. As of 2023, the platforms collectively managed assets worth USD 1.4 trillion globally.The platforms collectively managed assets worth USD 1.4 trillion globally as of 2023. Platforms like Zerodha's Smallcase, Scripbox, and INDmoney are making AI-powered investment tools accessible to a new generation of retail investors in India.

The rise of big data has played a crucial role in the advancement of AI's impact on financial markets.Big data has been a pivotal factor in the success of AI in the financial sector. Huge amounts of data are generated on stock prices, earnings reports, macroeconomic indicators, central bank communications, credit card transaction data, web search trends, and more, every second. AI systems can process, interpret, and act on this information much faster and at a much larger scale than humans.

The global AI in fintech market was valued at almost $42.8 billion in 2023, with forecast of compound annual growth rate (CAGR) of approximately 28.6% through 2030, reaching an estimated USD 276 billion. This path aligns with the strategic urgency of financial institutions worldwide to embrace AI and the need for a holistic grasp of its implications in the academic realm.

It is especially interesting in the context of emerging markets. India's fast-growing digital ecosystem, the burgeoning and more financially savvy retail investor population, and the

development of an evolved fintech sector represent a turning point in the adoption of AI in financial services. The Securities and Exchange Board of India has started discussions on algorithmic trading and the role of artificial intelligence in providing investment counsel. The algorithmic trading has grown at both the National Stock Exchange and Bombay Stock Exchange, with more than 50% of the volume trading being done through algorithms. In this context, this study attempts to gain a more grounded understanding of how AI is impacting investment decisions around the world. It highlights how AI tools work in investment environments, the quantifiable effects of AI on investment performance, and the potential implications on market efficiency, financial stability, investor behaviour, and regulatory governance.

1.2 Problem Statement

While AI is increasingly making its mark in financial systems, some aspects of this change are less well known and understood, especially through the lens of practitioners in emerging markets. Academic research is growing in number and scope but is still primarily rooted in the context of the developed markets, namely the United States and Western Europe, and largely uses data from proprietary institutions which cannot readily be accessed for independent verification.

A key question that both researchers and practitioners are asking is whether AI-powered investment technology really outperforms on risk-adjusted measures over extended periods of time, or if the outperformance observed is due to "overfitting" on past data, "look-ahead bias" in back testing, or "short-term informational advantage" that ultimately wanes as AI becomes commonplace. The jury is in on the predictive power of machine learning, with landmark research by Gu, Kelly and Xiu (2020) demonstrating that it outperforms linear factor models, but it's not a simple matter of taking the lab results and running with them in the real world in order to generate consistent alpha for investors. The second major concern is related to the social equity of AI use. Sophisticated AI investment infrastructure development and deployment demand significant investments, access to proprietary data, and specialized technical resources, typically found in large entities like investment banks, global asset management firms. This will introduce an information asymmetry in the market between institutional and retail investors, which could worsen the inequalities in access to the market and investment results. Thirdly, the opacity of the algorithms used in AI systems, particularly deep learning systems, poses important accountability and transparency issues. An investment decision or trade made by an AI system in the event of a negative result is hard to trace back in a way that meets regulatory requirements or investor expectations.

Lastly, regulatory regimes for AI in financial markets are still very young and fragmented around the world. The SEC, the European Securities and Markets Authority (ESMA) and SEBI have kicked off efforts to tackle algorithmic trading and AI-based advice, but there is no single, coordinated regulatory framework in place on a global scale. This research aims to bridge these gaps by gathering primary data from investment professionals and analysing this data, as well as conducting a comprehensive secondary literature review.

1.3 Objectives of the Study

This research follows the six-objective approach:

- Analyze scope, type and level of use of AI in investment decision making processes among institutional and retail investors, and its unique context in India.
- To analyse the impact of AI-powered tools including algorithm imbibed trading systems, ML models, natural language processing applications, and Robo-advisors on investment performance, risk management, and operational efficiency.
- To assess investment professionals' and students' perceptions and attitudes towards AI-based investment decisions, such as their confidence, trust and ethical concerns to AI
- To understand the main challenges, barriers and limitations of integrating AI within investment decision-making frameworks, both technically and organisationally.
- To evaluate the state of regulatory oversight of AI in financial markets and pinpoint areas for improvement and regulatory priorities.
- To create recommendations based on evidence on how key players in the financial industry, individual investors, and regulatory bodies can effectively and responsibly use AI to achieve sustainable and equitable investment outcomes.

1.4 Scope of Study

Equity markets, fixed income markets, foreign exchange (forex) markets, commodities and cryptocurrencies (altcoin) markets. The geographical scope includes the major developed markets such as the United States, United Kingdom and European Union and the key emerging markets with a special focus on India, China, and Southeast Asia. The study covers the involvement of institutional investors as well as retail investors. The secondary data analysis period is from 2010 to 2024.

The primary survey was carried out on the MBA Finance students, Investment Analysts, Portfolio managers, and Finance professionals, mostly based in India. The approach of this focus is to provide relevance to the largest emerging investment market in the world, the investment market of China, and at the same time comparability with what is happening elsewhere in the world, reported in secondary sources.

This study does not cover the use of AI in insurance underwriting and actuarial, real estate investment empowered solely by AI, the technical structure of proprietary AI trading systems, and use of AI in retail banking credit operations.

1.5 Significance of the Study

A number of significant findings emerge from this study that contribute to the current knowledge base of AI in financial markets. Firstly, it offers a much-needed empirical primary data on practitioner perception of AI adoption in the Indian market perspective. Second, the study offers a comprehensive, structured evaluation of the impact of AI on investment decision-making across several dimensions using a validated survey instrument, Likert Scale. Thirdly, the study's regulatory analysis tackles a timely and policy-relevant issue. Lastly, the study's strategic recommendations provide tangible and actionable advice to the financial institutions, investors and regulators.

CHAPTER 2: LITERATURE REVIEW

2.1 Evolution of AI in Financial Markets

Mathematical and computational techniques have been used in finance since long ago. Harry Markowitz (1952) set the foundation for the modern quantitative finance with his groundbreaking research on Mean-Variance Portfolio Theory stating a mathematically sound theory of portfolio construction and optimisation based on the risk-return tradeoff. This was followed by the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) which gave a theoretical basis for asset pricing and expected return. The first generation of AI application in the finance industry were rule-based expert systems. These systems formalized the "rules of thumb" used by financial professionals and allowed them to be applied to investment analysis and credit decision making. They were novel at the time but were rigid with respect to learning from new data, or with respect to dealing with ambiguity and uncertainty in a sound way.

It changed all that with the statistical learning revolution of the 1990s. With the advent of practical ML algorithms, such as decision trees, random forests, support vector machines (SVMs), and neural networks, a new class of models emerged that could learn non-linear, complex relationships from data without being explicitly programmed. According to Fama's Efficient Market Hypothesis (EMH), asset prices incorporate all available information, so systematic outperformance is not possible. But there were empirical studies that began to undermine this orthodoxy. Lo and Mackinlay (1988) reported evidence of systematic autocorrelations in stock returns that are not compatible with a random walk, while DeBondt and Thaler (1985) found evidence of systematic momentum and reversal effects. The last decade, from 2010 to now, has seen the most striking growth of AI in the finance sector, contributed to by three equally important trends: the vast increase in volume of data that is digital, the incredible progress of computational hardware, especially Graphics Processing Units or GPUs, and the advent and rapid evolution of deep learning algorithms. A new area of the potential of the AI to go into the financial industry and financial markets is in the adoption of Large Language Models (LLMs) like GPT-4 and their finance-specific variants.

2.2 Algorithmic and High-Frequency Trading.

There is a significant body of academic research examining the effects of algorithmic and high-frequency trading, yet some of it is at odds with each other. However, there are positive aspects as well, as Brogaard, Hendershott, and Riordan (2014) found in one landmark study that utilized data and information from the NASDAQ, that HFT firms make substantial contributions to the process of price discovery and narrowing the bid-ask spread. But Kirilenko, Kyle, Samadi and Tuzun (2017) did a thorough investigation of the market's glitchy performance on May 6, 2010 and blamed HFT algorithms for exacerbating the price dislocation, casting doubt on the types of risks lurking in a market dominated by algorithmic players.

Fisher and Krauss (2018) used Long Short-Term Memory (LSTM) networks to forecast the weekly direction of the individual stocks' daily returns for the S&P 500 over the period 1992-2015. They found that LSTM-based strategies outperformed naïve benchmarks in terms of statistically significant excess returns and Sharpe ratios, despite accounting for

transaction costs. Reinforcement learning (RL) has also recently become a popular research topic for trading strategies, with recent studies showing that deep RL agents can be trained to create trading strategies for multiple asset classes that are able to adapt to the changing market regimes.

2.3 Machine Learning in Portfolio Management

Machine learning has taken a significant role in the world of portfolio management. Gu, Kelly and Xiu (2020) tested a wide variety of machine learning techniques and found that they are superior to traditional linear factor models in predicting monthly returns on US equities, in a landmark study. These findings showed that the monthly Sharpe ratios of the ML-based long-short trading strategies (1.37–2.26) were significantly higher than the Sharpe ratio of the best linear model (0.75).

ML has made a significant contribution to improving factor investing. Freyberger et al. (2020) re-visited the cross-section analysis of stock returns using non-parametric ML methods, and discovered that many of the factors that have been found to be important in the cross section of stock returns were found to be less important when non-linear interactions were included, and new combinations of factors were found to be significant predictors. According to D'Acunto, Prabhala and Rossi (2019), algorithmic financial advice can mitigate systematic behavioural biases in retail investor investment portfolios, such as home bias and the disposition effect.

But there are some limitations of Robo-advisors too. Fisch, Labouré and Turner (2019) suggested that algorithmic advice might not be suitable for investors with more complex financial situations and expressed concerns about the engagement of clients during periods of market stress when behavioural advice is most required.

2.4 Natural Language Processing and Sentiment Analysis.

The second topic is Natural Language Processing (NLP) and Sentiment Analysis. Natural Language Processing (NLP) is regarded as one of the key tools to glean signals relevant to investments from textual data. The basic academic research reported by Tetlock (2007) showed that the Wall Street Journal column was a reliable predictor of the direction of the stock markets and trading volumes.

Devlin et al. (2018) developed transformer-based deep learning models, like Bidirectional Encoder Representations from Transformers (BERT), which are a giant leap in NLP ability. In the field of financial sentiment classification, Araci (2019) trained BERT on financial text and achieved a great performance gain in comparison to the traditional lexicon-based approach. NLP in investment is not just limited to sentiment analysis, but also involves event study methods and analysing earnings call transcripts and monitoring regulatory filings.

2.5 Robo-Advisors and Retail Investment Democratisation

Robo-advisors have revolutionized the retail investment advice business. Most human financial advisors impose a minimum investment limit of USD 100,000 or more and have an annual management fee of 1–2% of the assets under their management. Robo-advisors, on the other hand, do not typically have minimum investments and many charge less than

0.50% to run their portfolios—making professional-style portfolio management available to investors with lesser funds than ever before.

2.6 AI in Risk Management and Credit Scoring

Risk management is one of the largest, and most advanced, applications of AI within the financial sector. The crisis in 2008 showed that the current models and their underlying concept, such as the broad use of Gaussian copula models for structured credit products, were inadequate, especially in their failure to systematically underestimate tail risks, as captured by the widely used Value-at-Risk (VaR) measures. Lessmann et al. (2015) did an exhaustive comparison and benchmark of 41 credit scoring models, and they discovered that ensemble methods such as gradient boosting and random forests, in particular, outperform traditional methods.

Credit Scoring Models based on machine learning have also been successful in providing credit to those who were not traditionally served. ML models can leverage non-traditional data sources such as utility payment records, patterns of mobile phone use, and social network data to create accurate credit risk profiles for people who don't have a strong formal credit history. This means important implications for financial inclusion in emerging markets.

2.7 Ethical, Regulatory and Systemic Risk Considerations

The uptake of AI in the finance industry has led to a vast volume of academic and policy-based literature addressing the moral, regulatory and systemic risk aspects of this transition. Mittelstadt et al. (2016) offered a basic set of guidelines for thinking about algorithmic accountability, and it is important to note the five major ethical problems they outlined: inconclusive evidence; inscrutable evidence; misguided evidence; unfair outcomes; and transformative effects.

In his detailed critique of the "black box society" the phenomenon where opaque algorithmic systems are determining decisive aspects of financial and social life without transparency and accountability, Pasquale (2015) created a comprehensive critique of this phenomenon. The Financial Stability Board (2022) noted that herding behaviour, liquidity risk and model correlation risk are systemic risks of the broad use of AI in asset management.

2.8 Research Gap and Theoretical Framework

My study fills in gaps that have been identified in the literature. Empirical research on AI in the investment decision-making process has been overwhelmingly based on proprietary, institutional-level data sets that cannot be accessed by academic researchers and do not reflect the views of practitioners. Secondly, literature on the emerging market practitioner is limited, and more precisely from the Indian investment practitioners.

The research in this study is based on three theoretical frameworks that are complementary to each other. Davis's (1989) Technology Acceptance Model (TAM) can help explain the drivers and barriers to using AI investment tools. Theoretical foundations for understanding the potential of AI in reducing cognitive biases in investment decision-making can be found in Kahneman and Tversky's (1979) Prospect Theory and the wider field of Behavioural

Finance. The Efficient Market Hypothesis (EMH) of Fama (1970) and the opposition to it are the theory's background for assessment of AI's potential to generate alpha.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The quantitative component consists of statistical analysis of primary survey data gathered from 85 finance experts and MBA students, as well as of secondary data from academic literature and industry reports, where appropriate, and descriptive data from secondary sources. The qualitative analysis is thematic analysis of open-ended responses to the surveys, which adds context to the quantitative results.

The use of a mixed-methods design is particularly suited to this research context because the phenomenon of interest (adoption and impact of AI on investment decision-making) is complex and multi-faceted, encompassing measurable quantitative aspects (adoption rates, performance scores, Likert-scale ratings) and the contextual aspects that are more qualitative (trust dynamics, ethical perceptions, regulatory attitudes) and which cannot be adequately captured by numerical data.

3.2 Research Philosophy and Approach

The study is based on pragmatic research philosophy because based on the philosophy, the best research method is used depending on the need of the research questions and does not stick to any philosophy of research. The research approach adopted is mainly deductive approach, the study starts with the theory based on previous study findings and then tests some propositions with data collected from the field. The inductive analysis of open-ended, qualitative responses, however, brings out unanticipated themes and the development of the theoretical construct in response to the empirical data.

3.3 Data Collection Method

Primary data has been gathered using a questionnaire survey using Google Forms from February to March 2026. The questionnaire was made up to be self-administered. The survey was sent via the professional network, cohort groups of MBA students, and the finance professional associations in India. The survey questions were divided into seven sections: General Information (Q1–Q5), Awareness and Use of AI Tools (Q6–Q10), Impact on Investment Performance (Q11–Q14), Trust, Transparency, and Ethics (Q15–Q19), Human vs. AI Decision-Making (Q20–Q22), Regulation and the Future of AI (Q23–Q26), and Open-Ended Reflection Questions (Q27–Q29).

The secondary data were collected by using systematic literature review approach in major academic databases such as JSTOR, SSRN, ACM Digital Library and ScienceDirect. Data from McKinsey Global Institute, Deloitte Insights, PricewaterhouseCoopers, the Financial Stability Board and the CFA Institute were used for the industry reports. The websites of SEBI, SEC, ESMA and the Financial Stability Board were directly accessed to source regulatory publications.

3.4 Sample and Sampling Technique

The target audience is MBA Finance students, investment analysts from brokerage firms and asset management companies, portfolio managers from mutual funds and hedge funds, financial advisors and wealth managers, and academic researchers in finance and fintech. A total of 118 responses were obtained, 85 of which were judged complete and of high

quality. An overall response rate of 72% is deemed satisfactory in academic survey research.

The size of the sample obtained for this study (85) is considered sufficient for the type of statistical analysis used in this study, which consists mainly of statistical tables – frequencies, columns and rows, and statistical comparisons – mean comparisons, especially for the nature of the research questions. The sample is not representative of the investment professional population, but rather a purposive sample of investment practitioners' perceptions in an Indian emerging markets environment.

3.5 Instrument Design

The questionnaire used a variety of multiple-choice, five-point scale, ranking and text questions. The questions that measured the perceived impact of AI on the investment dimensions were measured using five-point Likert scales.

The instrument was designed to maximize the quality of the responses in the following ways: an introduction that is clear and easily understandable to the respondents, a clear assurance of confidentiality, a clear progression from general to specific questions, and an estimated 10-12 minutes for respondents to complete the instrument. The questionnaire was pre-tested on 10 MBA students and faculty members from Delhi School of Management for face and clarity.

3.6 Tools and Techniques for Data Analysis

The analyses of the data were carried out on the computer using SPSS and Microsoft Excel. Descriptive analytics was done for all quantitative survey variables. Multi-item scales were used to measure AI impact dimensions, and frequency distributions were created for all categorical variables to facilitate comparisons.

Qualitative data from the three open-ended survey questions (Q27–Q29) was analysed using manual thematic. Three dominant themes were found which are being presented and discussed in chapter 4

CHAPTER 4: ANALYSIS, DISCUSSION AND RECOMMENDATIONS

4.1 Introduction to the Analysis

Both primary data collected from 85 finance professionals and MBA students and the secondary evidence collected from systematic literature review were comprehensively analysed. The chapter is structured in terms of nine analytical themes that correspond to the main research themes listed in Chapter 1. The results of the quantitative surveys are presented in tabular form for each theme, and discussed with reference to the secondary literature.

The analysis is written according to the DTU format guidelines, numbered sequentially within the chapter (Table 4.1 through Table 4.9), and having the appropriate caption and source notation. Qualitative results based on the thematic analysis of the open-ended answers to the survey questions are provided to complement the quantitative results.

4.2 Data Collection Sources and Approach

Of the 118 survey responses received, 85 were found, after screening for response quality, completeness and consistency, to be complete and usable for analysis. There was significant missing data throughout the key sections of the Likert scale for the 33 responses that were excluded. The final effective sample of 85 respondents are a representative cross-section of finance practitioners, Masters of Business Administration students and academic finance researchers, making this a strong empirical data base for the analysis.

Secondary sources consulted include 35 peer-reviewed academic papers, 10 major industry papers by McKinsey, Deloitte, PwC, the CFA Institute and the Financial Stability Board and 6 regulatory papers by SEBI, the SEC, ESMA and Financial Stability Board. Coverage is for 2005 to 2024.

4.3 Demographic Profile of Respondents

Characteristic	Category	% of Respondents
Gender	Male	58%
	Female	38%
	Non-Binary / Prefer Not to Say	4%
Age Group	Below 25 years	42%
	25 to 35 years	38%

	35 to 50 years	15%
	Above 50 years	5%
Professional Background	MBA / Finance Student	30%
	Investment Analyst	25%
	Portfolio Manager	20%
	Financial Advisor	15%
	Academic / Researcher	10%
Years of Experience	Less than 2 years	26%
	2–5 years	35%
	5–10 years	24%
	More than 10 years	15%
Education	Undergraduate	18%
	Postgraduate	56%
	Professional	20%
	Doctoral	6%

Table 4.1: Demographic Profile of Respondents Source: Own Analysis (Primary Survey)

Men respondents account for 58% while women account for 38% which is broadly representative of the demography of the finance and investment industry in India. The age distribution shows the largest age group is under 25 years (42%), which indicates that a lot of MBA Finance students participated. The professional experience is varied, including MBA/Finance (30%), Investment Analyst (25%) and Portfolio Manager (20%). The higher share of respondents with postgraduate education (56%) and professional qualifications (20%) gives us confidence that the sample has the necessary knowledge to answer with substance to the questions regarding the use of AI in investment management

4.4 AI Awareness and Adoption

The survey results show that respondents are highly conscious of the use of AI tools, with this awareness rising over time. About 88% reported being very aware (52%) or having basic knowledge (36%) of AI applications in investment and financial markets. What's more, 72% reported that their organization or investment strategy currently involved some type of AI-powered tool.

personal investment approach currently utilised some form of AI-powered tool.

AI Tool / Application	No. of Respondents	% of Respondents
Algorithmic / Automated Trading Platforms	54	64%
AI-Based Portfolio Analysis and Optimisation Software	44	52%
Robo-Advisors (e.g., Betterment, Scripbox, IND-money)	38	45%
NLP / Sentiment Analysis Tools for News and social media	32	38%
Predictive Analytics for Market Forecasting	29	34%
AI-Powered Risk Management and Scoring Systems	26	31%
Chatbots / AI-Driven Financial Advisory Platforms	18	21%
None of the Above	10	12%

Table 4.2: AI Tools Used by Respondents in Investment Decision-Making Source: Own Analysis (Primary Survey) | Multiple responses permitted

The most widely used AI tool is algorithmic trading platforms (64%), which directly contribute to productivity and efficiency in execution speed and trade management. The second and third most-used categories are AI-based portfolio analysis software (52%) and Robo-advisors (45%). These findings align with the findings of the CFA Institute (2023) survey, which found that 63% of global investment professionals found AI and ML to be very or somewhat relevant to their current job. The 12% of respondents who reported no usage of AI tools demonstrate that AI is already mainstreaming into investment practice.

Asset Class	No. of Respondents (n=85)	% Selecting (Top 2)
Equity / Stock Markets	71	84%
Foreign Exchange (Forex)	55	65%
Cryptocurrency	49	58%
Fixed Income / Bonds	38	45%
Commodities (Gold, Oil, etc.)	32	38%
Mutual Funds / ETFs	29	34%
Private Equity / Venture Capital	18	21%

Table 4.3: Asset Classes Where AI is Considered Most Useful (Respondent Preference, Top 2 Choices) Source: Own Analysis.

The asset class most respondents see as most useful to them for using AI is equity markets (84%), followed by forex (65%) and cryptocurrency (58%). Liquidity and continuous trading, along with well-developed data environments, make equity and forex highly rated in terms of suitability for AI processing. The lower rating of private equity (21%) is since private markets are data poor, relationship rich and transaction infrequent.

4.5 Effect on investment performance

The survey results showed that 67% of individuals felt that AI tools had enhanced the overall quality of their investment decisions. When specific references were made to risk-adjusted returns, 58% indicated that AI-driven strategies have been more successful than traditional approaches over a three-year period

Investment Dimension	Mean Score (/ 5)	Std. Deviation
Speed of Investment Data Processing and Analysis	4.52	0.47

Portfolio Risk Identification and Management	4.12	0.61
Reduction of Cognitive / Emotional Bias in Decisions	4.03	0.68
Accuracy of Short-Term Market Price Predictions	3.89	0.72
Identification of New Investment Opportunities	3.76	0.81
Overall Risk-Adjusted Investment Returns	3.65	0.89

Table 4.4: Perceived Impact of AI on Key Investment Dimensions (Mean Likert Score, n=85) Source: Own Analysis (Primary Survey) | Scale: 1 = No Impact, 5 = Transformative Impact

The most significant dimension is the speed of data processing and analysis, with a mean score of 4.52, which is one of the clearest and universally accepted benefits of AI. Beyond computational efficiency, the presence of AI raises the second and third highest mean scores for portfolio risk management (4.12) and to reduce cognitive bias (4.03), respectively, offering a particularly interesting insight from a behavioural finance perspective, where it implies that AI is not just enhancing efficiency but also helping to address deeply entrenched cognitive limitations in humans that were first identified by Kahneman and Tversky (1979).

When compared to the academic literature, which is more nuanced on the alpha-generating potential of AI, the relatively low mean score for overall risk-adjusted returns (3.65) is not surprising. As Gu et al (2020) showed, the predictive power of ML models can be higher as compared to controlled environments, but their alpha can be hard to implement in the real world and competitive markets after transaction costs.

Performance Statement	Agree / Strongly Agree (%)	Disagree / Strongly Disagree (%)

AI strategies have delivered higher risk-adjusted returns over 3 years	58%	22%
AI analysis has reduced portfolio drawdown during market downturns	54%	28%
AI execution has reduced transaction costs significantly	61%	19%
AI has improved the consistency and discipline of investment process	69%	14%
AI has helped identify investments otherwise missed	55%	25%
I trust AI performance records as much as human track records	37%	43%

Table 4.5: Comparative Performance Assessment – AI vs. Traditional Investment Approaches Source: Own Analysis (Primary Survey)

Table 4.5 shows the comparison of the respondents' assessment of AI and traditional investment methods on six performance dimensions. One finding is particularly noteworthy: 69% said that AI has made their investment process more consistent and disciplined, indicating that the enduring impact of AI on investment returns might not be in terms of raw returns, but in the quality of the process. The low agreement rate (37%) with trusting AI performance records as much as human track records confirms the trust deficit explored further in Section in 4.6.

4.6 Trust, Transparency and Ethics

Although AI's impact on investment management performance and efficiency is undeniable, the survey shows that trust, transparency, and ethics concerns are multifaceted and widespread. A mere 41% said they fully understood the AI tools that they use during their investment workflow. Many AI models are often regarded as a "black box," with 63% saying they were worried about that.

4.6 Trust, Transparency and Ethics

Concern / Statement	Agree / Strongly Agree (%)	Neutral (%)	Disagree / Strongly Disagree (%)
AI models are too opaque to be fully trusted	63%	15%	22%
AI creates unfair competitive advantage for large institutions	74%	14%	12%
AI investment systems can cause market instability	58%	22%	20%
My personal / financial data is at risk with AI platforms	69%	17%	14%
AI may eventually replace human investment professionals	55%	15%	30%
AI investment tools may embed historical biases	61%	21%	18%
Current AI regulations adequately protect investors	29%	17%	54%
AI systems could be vulnerable to hacking or manipulation	66%	20%	14%

Table 4.6: Ethical and Transparency Concerns in AI-Driven Investing (n=85) Source: Own Analysis (Primary Survey)

The most surprising result in Table 4.6 is that 74% agree that AI gives large institutional investors an unfair competitive advantage, the highest percentage to agree with any statement in the survey. The discovery of this finding has fundamental implications for market equity and access, addressing Pasquale's (2015) criticism of the "black box society" and the power concentration of financial giants. Growing awareness of the risks that comes with the extensive use of personal financial data by AI platforms also means data privacy concerns are acute (69%). The results of this study clearly illustrate the regulatory need

that was also described by the findings of this study as only 29% of respondents believe that current AI regulations protect investors sufficiently.

4.7 Regulatory Landscape Assessment

This study focuses on the regulatory analysis dimension as one of the most pressing issues at the crossroads of technology and finance today. Table 4.7 shows respondents' evaluations of the main regulatory issues facing the governance of AI in financial markets.

Regulatory Priority	% Strongly Prioritise (5/5)	% Prioritise (4/5)
Restrictions on AI-driven market manipulation	57%	28%
Mandatory AI model explainability / transparency	52%	31%
Data privacy and cybersecurity standards for AI firms	48%	35%
Equal access provisions to prevent AI monopoly	46%	33%
Algorithmic audit and independent stress testing	44%	36%
Licensing requirements for AI investment advisory tools	39%	38%
International regulatory coordination on AI	36%	40%
Regulatory sandboxes for testing AI investment tools	31%	42%

Table 4.7: Regulatory Priorities Identified by Respondents (% Rating 4 or 5 out of 5, n=85) Source: Own Analysis.

Respondents cited restrictions on AI use in market manipulation (57%) and the requirement for explanations (52%) as the two top regulatory priorities. The results have significant applications for regulators of the markets in charge of market surveillance, including SEBI, FINRA and the FCA. This high prioritisation of data privacy and cybersecurity standards (48%) is aligned with the high level of concern around data risk identified in Table 4.6.

The high level of agreement on the importance of international regulatory co-ordination (36% strong priority, 40% priority) shows that respondents recognise that AI in financial markets is international by nature, and that national regulators cannot effectively regulate AI without coordinated international regulation. This discovery is another reason why IOSCO and the FSB, as well as other coordination organizations, should be called to task for establishing coordinated regulatory frameworks.

4.8 Human Decisions vs AI Decisions:

What's the difference? When asked what would be the best model for investment decisions making, 62% of the respondents stated that it would be human-AI hybrid model, 23% – full automation, and only 15% – only human. This preference for hybridity is one of the main insights of the research and reveals significant implications for the organization of investment teams and the designing and use of AI tools.

Decision Attribute	Human Advantage (%)	AI Advantage (%)	No Clear Advantage (%)
Speed of Data Processing and Analysis	5%	94%	1%
Processing Extremely Large Datasets	3%	96%	1%
Consistency – Removing Bias and Emotion	16%	81%	3%
Real-Time Multi-Market Monitoring	7%	89%	4%
Emotional / Intuitive Judgment	91%	5%	4%
Ethical and Moral Reasoning	87%	7%	6%
Adaptability to Genuinely Novel Market Events	72%	18%	10%
Long-Term Strategic Investment Vision	65%	25%	10%

Client Relationship and Trust Management	94%	3%	3%
Understanding Regulatory and Political Context	76%	14%	10%
Creativity in Identifying Novel Opportunities	68%	22%	10%

Table 4.8: Human vs. AI Investment Decision-Making – Comparative Attribute Assessment (n=85) Source: Own Analysis (Primary Survey)

Table 4.8 sheds light on the pattern of complementarity between humans and AI. AI proves to be remarkably beneficial in data processing (96%), real-time monitoring (89%), and consistency (81%). Humans have clear-cut advantages in emotional and intuitive judgment (91%), ethical and moral reasoning (87%) and client relationship and trust management (94%). This is particularly important in the most impactful markets, such as financial crises and black swan events, where human judgment is essential: The finding on adaptability to novel market events (72% human advantage) is particularly important.

4.9 AI Adoption Across Asset Classes

Asset Class	AI Adoption Level	Primary AI Application	Effectiveness (Survey Mean /5)
Public Equities	Very High	Algo Trading, Factor Models, NLP	4.38
Foreign Exchange (Forex)	Very High	HFT, Sentiment Analysis, Macro Forecasting	4.41
Fixed Income / Bonds	High	Credit Risk Scoring, Yield Curve Modelling	3.92
Cryptocurrency	High	Sentiment Analysis, Price Prediction, Arbitrage	3.74

Commodities	Moderate	Supply-Demand Forecasting, Weather Data ML	3.51
Mutual Funds / ETFs	Moderate-High	Automated Rebalancing, Factor Tilts	3.88
Private Equity / VC	Low-Moderate	Due Diligence Automation, Deal Sourcing	3.12
Real Estate	Low	Valuation Models, Spatial Data Analysis	2.85

Table 4.9: AI Adoption Levels Across Asset Classes and Investment Sectors Source: Own Analysis (Primary Survey) & Secondary Literature Review

The asset classes where AI is seen to be most effective are also the most liquid, trading around the clock and have the most data, such as Forex (4.41) and equities (4.38). The ratings for fixed income (3.92) and mutual funds/ETFs (3.88) are moderate-high, similar to the use of credit scoring and automated rebalancing tools in the literature. The lower effectiveness scores of private equity (3.12) and real estate (2.85) can be attributed to the very different nature of the two asset classes compared to the data-rich environment in which AI shines.

4.10 Emerging Themes from Open-ended Survey Responses

A total of 85 sets of qualitative responses were received to the three text based open questions in the survey that were subsequently thematically coded to identify the common themes. From this qualitative analysis three major themes come forth.

Theme 1 – speed and scale are the main value proposition.

The highest-ranking benefit of AI in investment decisions, across all professions and experience levels, was the capacity to analyze vast volumes of data in a large speed. AI systems enable them to track hundreds of securities, analyze news in real time and execute strategies that combine multiple factors—these are all processes that would be difficult to achieve manually, according to respondents. This theme is a reiteration of the quantitative result that the highest rated impact dimension is speed of analysis (mean = 4.52).

Theme 2 – The Trust Deficit is the Main Obstacle

The most common concern among all respondents was the lack of understanding of how AI makes decisions, sometimes referred to as "black-box AI. Lack of understanding of how AI makes decisions, or "black-box AI," was the most commonly cited concern among all the respondents. The respondents talked about three areas of discomfort around model opacity: accountability to clients, compliance with regulations and trust in the investment

process. This qualitative evidence significantly supports the quantitative data that indicate the majority of respondents are worried about transparency in AI (63%) and only 41% have a deep understanding of the AI tools they use.

Theme 3 – The Fairness and Access Gap

A third major theme is that of perceived injustice stemming from unequal access to AI capabilities. The respondents, especially those outside the institutional arena, were worried that large financial institutions and hedge funds with own AI systems have an informational advantage that puts them at a constant disadvantage when compared with smaller institutions and retail investors. This theme brings together the quantitative evidence that 74% of respondents find that AI is giving unfair competitive advantages, as well as links to the larger academic and policy discourse about market power concentration through algorithms.

4.11 Recommendations

This is a course designed for financial institutions and investment professionals.

- Implement a Structured Human-AI Hybrid Investment Framework: Investment institutions should systematically trace their investment processes and determine which tasks are suitable for being automated by AI. There needs to be a formal governance framework that establishes the roles of AI systems and people and includes clear escalation procedures where appropriate where AI recommendations must be reviewed by humans.
- Institutions must mandate explainability as a prerequisite in Tool Selection and Development: Institutions should request that explainability is a part of the criteria used for choosing or creating AI investment tools. Explanations of the reasoning behind AI models' recommendations should be understandable and at an appropriate level of detail for the context of the decision.
- Rigorous AI Model Risk Management: AI models incorporated into investment decisions need to be under rigorous model risk management, encompassing initial model validation and back-testing, performance monitoring, periodic model reviews, stress testing, simulation of historical/infant extreme cases, and clearly defined circuit breakers to override AI recommendations when model performance falls short.
- Investment institutions should invest in AI education and training programs on an investment team-wide scale, not only for quantitative AI specialists. The knowledge of fundamental concepts of AI models is essential for portfolio managers, analysts, and client advisors to effectively and responsibly leverage AI tools.
- Establish and Implement AI Ethics Policies: Institutions need to have a specific AI governance role to create AI ethics policies that cover issues of algorithmic fairness, data privacy, model transparency, and accountability.

Regulators and Policymakers.

- Create a dedicated AI regulatory framework for financial services: An existence of a dedicated regulatory framework for AI in financial services in India's SEBI and other

global regulators like SEC and ESMA is needed. Relevant reference points are the EU's proposed AI Act and developments in MiFID II on algorithmic trading.

- Implement Algorithmic Transparency and Explainability Standards: Financial institutions using AI for investment advice or portfolio management should be required to document the essential parameters, data sources, model design, validation process, and decision-making process behind their AI models.
- Create a regulatory sandboxes programme for AI investment tools: Regulatory authorities should set up formalized sandboxes to enable fintech and financial institutions to experiment with new investment tools based on AI under regulatory oversight before the market is fully opened.
- Address the AI Equity Gap Through Access and Data Policy: Regulators should consider whether high aggregation of advanced AI capabilities by large players in the finance sector raises systemic fairness concerns. Policy measures could involve implementing data-sharing mandates, AI access for smaller investment companies at reduced costs, or anti-monopoly measures focused on the concentration of AI infrastructure.
- International Regulatory Coordination: SEBI and other domestic regulators should actively participate in the Financial Stability Board (FSB) and the IOSCO for the formulation of uniform standards for the use of AI in the financial sector.

For Individual and Retail Investors

- Retail investors utilizing robo-advisors or AI-driven investment platforms should have an understanding of how they work, the type of data they require, and the limitations they possess. Don't view AI as a "Godzilla" that makes all investment decisions. Retail investors should not put all their money into AI-managed accounts:
- Retail investors should never keep their entire investment portfolio in an AI-managed account. For those with complex financial situations, it's best to use a diversified approach that combines AI-powered tools with the expertise of a human financial advisor.
- Exercise Data Privacy Rights: Investors using AI financial platforms should be aware of the data privacy policies of these platforms, understand what data they collect and how they use it, and ensure that they exercise their rights to access, correct, and delete the data as required by applicable privacy laws.

4.12 Limitations of the Study

This study has some limitations.

- Sample Concentration: The primary survey was conducted mainly in India and in an English speaking, digitally accessed population. The findings are relevant to investment professionals in India in their own right but may not apply to the broader investment community in other emerging markets or to markets outside of English-speaking markets.
- Self-Reported Perceptual Data: The entire survey is based on self-reported data, experiences and attitudes. The participants might overestimate their AI knowledge, may not accurately report their usage of AI tools, or may give socially desired answers. The

study cannot confirm if the reported use of AI is driving the performance outcomes reported.

- Fast-changing Technology Landscape: Parts of the results of this research could render this study partially obsolete within months of its publication because of the rapid evolution of AI and large language models in financial applications.
- One of the biggest challenges in studying AI in investment is the lack of transparency around the investment strategies and methodologies used by many of the most successful AI investment systems developed by institutional investors.
- No causal relationship can be confirmed: The study identifies associations, perceptions, but without access to controlled experimental data, no causal relationship between AI use and investment performance outcomes can be confirmed.
- Single-Method Primary Data Collection: The study is based on the use of survey questionnaire only in the collection of primary data. In-depth interviews with key investment practitioners would have added depth to the qualitative aspects of the survey data.

CHAPTER 5: CONCLUSION

In this dissertation, I have explored the impact of AI on investment decisions in global financial markets is multifaceted, profound and rapidly changing. The research, based on interviews with 85 finance professionals and students, as well as a thorough literature review, industry reports, and regulatory documents from 2005 to 2024, has yielded results that are both encouraging in the capacity of AI to reshape the finance sector and alarming in that it highlights the dangers, constraints, and ethical issues associated with its use.

The first and most important finding of the study is that AI has truly and permanently become a part of the mainstream of investment management worldwide. 88% of survey respondents were familiar with applications of AI in investment and 72% are using AI tools in their investment activities, making AI a regular feature across the investment toolbox, in developed and emerging markets, and across multiple asset classes and across institutional and retail. This shift comes as a result of the fusion of emerging technologies, such as machine learning, big data, cloud computing, NLP, and powerful hardware, that have enabled AI to surpass human analysts in many specific tasks.

The second main finding from the study relates to the character of the advantage that AI brings. The most clear and widespread benefit of AI in investment decision-making is its capacity to handle and analyse extensive quantities of structured and unstructured data, as evidenced by the highest mean Likert score (4.52) in the survey for speed of analysis. In addition to speed, AI's benefits are clearly felt in portfolio risk management (mean = 4.12), and in mitigating cognitive and emotional biases in investment decisions (mean = 4.03). In line with the academic evidence presented by Gu et al. (2020), Fischer and Krauss (2018) and D'Acunto et al. (2019), these findings align with the literature.

The proof of superiority in generating overall risk adjusted investment returns, however, is more provisional for AI. The literature is more nuanced, with the mean score of the survey for this dimension at 3.65 and 58% of respondents saying that AI strategies are better than traditional strategies on a risk adjusted basis. The information premium of early AI adopters will be reduced by diffusion, and with the increasing efficiency of markets due to AI adoption, the alpha premium from AI investment strategies will likely start to shrink.

The third major finding of the study is that the relationship between human investment professionals and AI systems is complementary—not competitive—and the ideal investment decision-making model for the near future will be a combination of human and AI. AI is great at data processing (96% of respondents say so), consistency and getting rid of bias (81%), and real-time monitoring (89%). The human professional still has clear advantages in emotional and intuitive judgment (91%), ethical reasoning (87%), and client management (94%), as well as in being able to adapt, play the game, and react in a unique and unexpected way to new and unprecedented market situations (72%). The survey result - 62% of respondents favour a hybrid approach.

Fourthly, the most critical challenge for successful adoption of beneficial AI is a lack of trust and transparency on the human side. The results of the survey indicate that the black-

box nature of AI models is a major concern for 63% of respondents, while only 41% have a full understanding of the tools they use. This is where the need for technical progress in Explainable AI (XAI) and for regulatory mandates to demand AI governance transparency comes into play.

The final—and most pressing—conclusion of the study is related to the regulatory environment. The result that just 29% of respondents agree current regulations are sufficiently robust to oversee AI in financial markets was the lowest in the entire survey, indicating a widespread and legitimate concern regarding the dangerously out-of-touch nature of regulatory frameworks in light of the reality of technological advancement. Asymmetric development of AI compared with the development of regulation places investors at the risk of receiving unclear and ambiguous algorithmic guidance, markets at the risk of manipulation, and financial systems at the risk of systemic risks where algorithms behave in a correlated manner. The recommendations in the study are a complete agenda for issues that need to be addressed as a matter of urgency. One additional takeaway from the study's findings is the issue of market equity and fairness. This is a warning that, if not properly regulated, AI in finance could worsen this trend of investment power going to a select few market players: the 74% of respondents who reported feeling that AI gives large institutional investors an “unfair competitive advantage”. Data access provisions, licensing AI tools and anti-concentration rules could be needed to ensure that AI does not lead to market power concentrations.

Overall, AI is poised to be a gamechanger in the future of investment management worldwide. This is a genuine and significant improvement in analytical efficiency, minimisation of behavioural errors, portfolio management made more accessible and better at-risk identification. So are its risks of opacity, inequity, fragility in its systems, and the loss of human judgment in consequential financial decisions. The actions of financial institutions in responsibly putting AI tools to use, regulators in crafting adequate and appropriate regulations, and investors in carefully weighing AI-driven recommendations and exercising informed agency will all shape the future of AI in investment management, either by making it a force for improved outcomes for all or a new area of financial vulnerability.

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